

Patch-based M3C2: Towards lower-uncertainty and higher-resolution deformation analysis of 3D point clouds

Yihui Yang^{*}, Volker Schwieger

Institute of Engineering Geodesy, University of Stuttgart, Geschwister-Scholl-Str. 24D, 70174 Stuttgart, Germany

ARTICLE INFO

Keywords:

3D point clouds
Deformation analysis
M3C2
Local consistency
Planar patches
Level of Detection

ABSTRACT

Multi-temporal acquisitions of 3D point clouds for geomonitoring tasks allow the quantification and analysis of geometric changes of monitored objects by advanced processing algorithms, further revealing the underlying deformation mechanism. Among numerous approaches proposed in the geoscientific domain for point cloud-based deformation analysis, multiscale model-to-model cloud comparison (M3C2) has been widely applied to quantify the distances between two point clouds with high surface roughness. Deformations under complex topographies, however, are still challenging to be accurately quantified and analyzed by a statistical significance test when using standard M3C2, for (1) average positions in the cylindrical neighborhoods may deviate from the actual surface and (2) empirical uncertainties represented by local roughness are overestimated in highly variable areas. Besides, the spatial resolution of derived deformations is limited by original point densities and algorithm limitations. In this article, we propose an alternative called patch-based M3C2, which inherits the basic framework of standard M3C2 for its simplicity. This novel data-driven approach does not need surface meshing and the identification of semantic or instance correspondences in point clouds. Lower uncertainty is achieved by generating locally planar patches and projecting measurements on associated patch planes, allowing better detection of small deformations in complex 3D topographies. Besides, patch-based M3C2 could assign a deformation value to any position within the overlapping areas, enabling a higher spatial resolution of deformation analysis. Our approach is demonstrated and evaluated on three datasets. The experimental results indicate that patch-based M3C2 exhibits higher accuracy on distance calculations between two surfaces.

1. Introduction

Multi-temporal 3D point clouds generated from laser scanning or photogrammetric techniques are widely exploited to reveal geometric surface changes in the real world (Qin et al., 2016; Stilla and Xu, 2023). Two-epoch point cloud comparison under a unified georeferencing frame can directly detect and quantify geometric changes of the monitored surface between monitoring epochs. In the field of engineering geodesy, we formulate this process as “point cloud-based deformation analysis” (Kuhlmann et al., 2014; Holst and Kuhlmann, 2016), where the term “deformation” herein, including both rigid-body movement and shape deformation, has equivalent implications to “change” used in the geoscientific domain. The analytical results of the former are typically displayed via displacement vectors, while the shape deformation could be directly reflected by the calculations of spatial distances or volume changes through point cloud comparison techniques (Girardeau-Montaut et al., 2005). To detect and quantify the significant deformations

between point clouds, numerous methods have been proposed and applied for monitoring infrastructural (Kermarrec et al., 2020), industrial (Holst et al., 2019), and environmental objects (Zhong et al., 2021). The adoption of specific algorithms depends on the objectives of deformation analysis (e.g., to obtain 3D displacement vectors or merely measure the spatial distances between two surfaces) and the geometric properties of acquired point clouds (e.g., point density, topographical complexity, surface roughness, etc.). Among these approaches to deformation analysis for 3D point clouds, however, uncertainties with respect to the quantified deformations are usually ignored or incorrectly estimated if there is no prior knowledge of a realistic stochastic model of the point cloud (Holst and Kuhlmann, 2016; Wunderlich et al., 2016). In addition, the spatial resolution of derived surface deformations may be reduced due to data characteristics or algorithm limitations. Aiming to cope with these challenges, this article presents a novel method called patch-based M3C2 (PB-M3C2) to quantify 3D distances and detect significant geometric changes between point clouds in the context of

^{*} Corresponding author.

E-mail address: yihui.yang@iigs.uni-stuttgart.de (Y. Yang).

<https://doi.org/10.1016/j.jag.2023.103535>

Received 24 October 2022; Received in revised form 10 August 2023; Accepted 20 October 2023

Available online 9 November 2023

1569-8432/© 2023 The Author(s). Published by Elsevier B.V. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

Table 1
Five categories of point cloud-based deformation analysis methods by correspondence definitions.

Methods	General principles	Limitations	Applicable scenes	Representative algorithms
Nearest neighbor-based Feature-based	Calculating EDs of the points in one point cloud (PC) to their nearest neighbors in another PC Calculating EDs of feature elements (e.g., points or planes) extracted and matched from two PCs or their converted 2D images	Deformation values are sometimes underestimated Low spatial resolution and incorrect correspondences in repetitive structures	Any point clouds Point clouds with distinct and corresponding features	C2C, C2M (Cignoni et al., 1998), M2M (Aspert et al., 2002) F2S3 (Gojcic et al., 2020), CD-PB M3C2 (Zahs et al., 2022), Image-based correlation (Travelletti et al., 2014), Image-based feature points (Holst et al., 2021) Geometric primitives (Yang et al., 2021), B-spline surface (Harmening et al., 2021)
Parameter-based	Calculating changes of parametric elements (e.g., centers of spheres) estimated by the parameterization of PC surfaces	Prior knowledge of global or local parameterization is required	Point clouds with geometric primitives, or parametric changes are required	DoD (Lane et al., 2003), M3C2 (Lague et al., 2013), M3C2-EP (Winiwarter et al., 2021)
Defined direction-based	Calculating EDs of constructed corresponding points from two PCs along defined directions (e.g., the gravity direction or surface normals)	Deformation values are under- or over-estimated if defined directions are inappropriate	Any point clouds with assumed deformation directions	Local ICP (Teza et al., 2007)
Local registration-based	Performing a registration procedure locally on selected subsets of two PCs to derive the transformation matrix and displacement vectors	Extracting corresponding rigid areas without prior knowledge is challenging	Point clouds with corresponding rigid areas	

complex surface topographies, based on the principle of the existing M3C2 algorithm (Lague et al., 2013).

1.1. Existing approaches to deformation analysis for 3D point clouds

Similar to point-wise geodetic monitoring, the prerequisites of point cloud-based deformation analysis are (1) registering two scans into one local or global coordinate system and (2) determining the corresponding elements within successive point clouds in explicit or implicit ways (Wunderlich et al., 2016; Gojcic, 2021). The Euclidean distances (EDs) of these correspondences are then calculated as the deformation values. Different from the categorization by other relevant literature (Qin et al., 2016; Neuner et al., 2016; Wunderlich et al., 2016; Harmening, 2020), herein we classify the existing strategies of point cloud-based deformation analysis according to their explicit or implicit definitions of correspondences that potentially indicate the deformation directions, as summarized in Table 1.

Among the above methods, the closest points between two point clouds are regarded as the correspondences in cloud-to-cloud (C2C) and local ICP, which are the exemplary algorithms of nearest neighbor-based and local registration-based methods, respectively. Cloud-to-mesh (C2M) or mesh-to-mesh (M2M) are based on the same principle but take the closest facet or edge in the triangulated mesh as the correspondence. The deformations calculated by this kind of correspondence, however, merely represent the minimum distances between two surfaces and may underestimate actual deformation magnitudes in variable surface topographies.

The feature-based methods are capable of finding realistic corresponding elements, so as to output actual surface displacement vectors. These algorithms are sensitive to both in-plane and out-of-plane deformations. Nevertheless, the correspondences like identical points within point clouds are either not measured between two scans or cannot be readily identified without prior knowledge (Wunderlich et al., 2016), especially when shape deformations or non-overlapping areas (i.e., the areas are not measured in all epochs) occur during geomonitoring. Gojcic et al. (2020) proposed feature-to-feature supervoxel-based spatial smoothing (F2S3) that introduces learned 3D feature descriptors instead of handcrafted feature points and establishes correspondences in the feature space. This neural network-based technique has dramatically improved the detection and matching of features in 3D point clouds from natural scenes. However, annotated training dataset incorporating ground-truth correspondences is needed, and smooth or highly deformed surfaces and surfaces with lots of repetitive structures are still challenging for this pipeline (Gojcic et al., 2021). Correspondence-driven plane-based M3C2 (CD-PB M3C2) proposed by Zahs et al. (2022) extracts individual planar surfaces from point clouds by region growing-based segmentation and establishes corresponding planes between epochs via a random forest classifier based on defined plane parameters (as similarity measures). M3C2 distances are then calculated between corresponding planes, and thus lower uncertainties can be achieved by benefiting from these segmented planes (Zahs et al., 2022). In addition, constructing correspondences in the converted 2D images from 3D point clouds based on digital image correlation (Travelletti et al., 2014) or feature detection in hillshade images (Holst et al., 2021) has also become an efficient way to derive dense displacement vectors. The converted image solely exploits the 3D coordinates of measured points, and thus its quality relies entirely on the point cloud.

The parameter-based methods are used to estimate parametric changes. The types of these parametric changes depend on the definitions of estimated parameters, which can be, for example, real displacements of geometric primitives when parameters are their 3D positions (Yang et al., 2021) or spatial distances between two approximating B-spline surfaces (Harmening et al., 2021). Due to the complexity of natural topographies, a complete and accurate parameterization of these surfaces is still challenging. Hence the spatial resolution of derived deformations from estimated parameters may be

reduced.

In the defined direction-based methods, correspondences are constructed implicitly along defined directions that are assumed to be consistent with the deformation directions. For example, DEM of difference (DoD) simply calculates the vertical distances of corresponding pixels of the generated DEM from point clouds (Lane et al., 2003). As one of the most commonly used algorithms for point cloud-based change detection, M3C2 adopts multi-scale to estimate the local surface normal and take it as the deformation direction. The correspondences are constructed by averaging the sub-clouds captured by a cylinder of which the axis is along the defined deformation direction (Lague et al., 2013). A variant of standard M3C2, called M3C2-EP, extends the estimation of the Level of Detection (i.e., LoDetection defined in Lague et al. (2013)) by error propagation that integrates intrinsic measurement uncertainties and non-uniform registration uncertainties to derive a more realistic LoDetection (Winiwarter et al., 2021). Notably, these defined direction-based methods are developed mainly for quantifying distances between point clouds rather than the real displacements on monitored surfaces. Nonetheless, the derived distance values have the potential to agree with the magnitudes of actual movements, provided reasonable definitions of deformation directions with prior knowledge. Besides, the spatial resolution of quantified deformations (distances) by defined direction-based methods will not be limited by the spatial coverage and distribution of feature-based or parameter-based correspondences.

1.2. Challenges for detecting small deformations in complex topographies

Natural scenes like landslides or rockslides normally display high variability and roughness and incorporate both rigid and non-rigid areas. The acquired multi-temporal 3D point clouds from geomonitoring procedures may contain varying point densities or data missing in non-overlapping areas due to occlusion and changes (Lague et al., 2013). Therefore, deformation analysis between these geomorphic surfaces requires accurate detection and quantification of deformations of different magnitudes under complex surface geometries and high measurement noise. Besides, calculations in non-overlapping areas should be avoided where spurious results may yield by the nearest neighbor-based methods. In addition, in the absence of prior knowledge of the stochastic model of point clouds, statistical significance tests can only be performed by empirically estimating the uncertainties of quantified deformations.

Among the existing approaches mentioned in Section 1.1, only M3C2 and its variants, to our best knowledge, could preferably meet the above demands. Nevertheless, the standard M3C2 has a limited capacity to detect small deformations due to its assumption of the local planarity of compared surfaces. For the surfaces with variable geometries and high roughness, the uncertainties of quantified deformations may be over-estimated and thus propagated into a higher LoDetection (Zahs et al., 2022). For instance, when monitoring a sandy beach by laser scanning, high-frequency (daily or even hourly) data acquisition should be conducted to adapt to the deformation rate of the surface (Anders et al., 2019). In such applications, the magnitudes of some captured deformations are small compared to associated LoDetection (over-estimated by local roughness), resulting in failed detection of these small deformations. As an extension of standard M3C2, M3C2-EP allows lower LoDetection for rough surfaces. However, additional inputs (e.g., sensor accuracy and scan positions) are required, and the cylindrical neighborhood continuously used in M3C2-EP may still estimate inaccurate average positions in rough areas (Winiwarter et al., 2021). Thereby, challenges still exist in M3C2 when detecting small deformations in highly rough surfaces.

The spatial resolution of quantified deformations herein refers not only to their spatial coverage and density but also to the capability to resolve the boundaries of deformation discontinuities. This is a critical quality feature to evaluate the performance of deformation analysis algorithms. Subsampled core points adopted in standard M3C2 to

accelerate the computation undesirably decrease the resolution of derived deformations. Another variant tailored for the geomonitoring of a rock glacier, CD-PB M3C2, enables much lower uncertainties and could derive real displacements by using feature planes as correspondences (Zahs et al., 2022). Like feature point-based approaches (e.g., F2S3), however, CD-PB M3C2 only computes deformations (displacements) in (assumed) rigid areas and takes the corresponding planes between epochs as the prerequisite. Therefore, the spatial resolution of quantified deformations by CD-PB M3C2 is reduced in non-planar or highly deformed areas.

Inspired by CD-PB M3C2, the proposed PB-M3C2, as a novel variant of M3C2, does not extract feature planes but divides the entire point cloud into small and planar patches and quantifies deformations (distances between two surfaces) via projected points on respective patch planes. Prisms are constructed from planar patches to capture correspondences instead of the cylinders in standard M3C2. Therefore, the uncertainties of detected deformations are lower than that by standard M3C2, while the spatial resolution is drastically improved compared to CD-PB M3C2.

2. Methodology

The general workflow of the proposed point cloud-based deformation analysis method is schematically shown in Fig. 1. Two-epoch point clouds (PC-1 and PC-2 are the point clouds captured from monitoring epoch 1 and epoch 2, respectively) are firstly divided into locally planar patches by supervoxel-based over-segmentation. Then we empirically estimate the standard deviations (i.e., *Std.* that will be defined in Section 2.1.2) of individual points by fitting a local plane of the corresponding patch, and then project the *Std.* in the direction of patch normals along the associated deformation directions defined by the user. These projected standard deviations (projected *Std.*) of two point clouds are further used to determine the LoDetection, considering a confidence interval and registration uncertainties. We quantify the deformations between two point clouds by PB-M3C2 distances based on the constructed prisms from patches instead of the cylinders used in standard M3C2. Finally, we detect the statistically significant deformations by comparing PB-M3C2 distances with the associated LoDetection. Details of PB-M3C2 are presented in the following subsections.

2.1. Patch generation by supervoxel-based over-segmentation

2.1.1. Local consistency assumption

In geodetic monitoring of natural scenes, the resulting deformations may present globally anisotropic directions and inhomogeneous magnitudes due to the inconsistencies of deformation mechanisms and the surface morphology of deformed objects but locally show a certain level of regularity (Gojčić, 2021). This kind of local consistency can be assumed within a specific neighborhood, including deformation directions and measurement uncertainties inside. Herein we define these local neighborhoods as piecewise and small patches that do not cross the discontinuities of deformations. Based on the local consistency assumption of deformed point clouds, calculations of deformation directions and empirical uncertainties of measured points are unified in respective patches. It should be emphasized that this local consistency assumption is the prerequisite for deriving PB-M3C2 distances and associated uncertainties.

2.1.2. Patch generation, modeling and refinement

The locally consistent patches could be generated by means of segmentation or clustering techniques based on the point similarities of spatial distance, local surface orientation, associated radiometric values (e.g., RGB colors and reflectance intensities), etc. Considering the performance and computational efficiency of relevant algorithms, we exploit the supervoxel-based over-segmentation strategy to partition 3D point clouds into locally planar patches, simultaneously preserving the

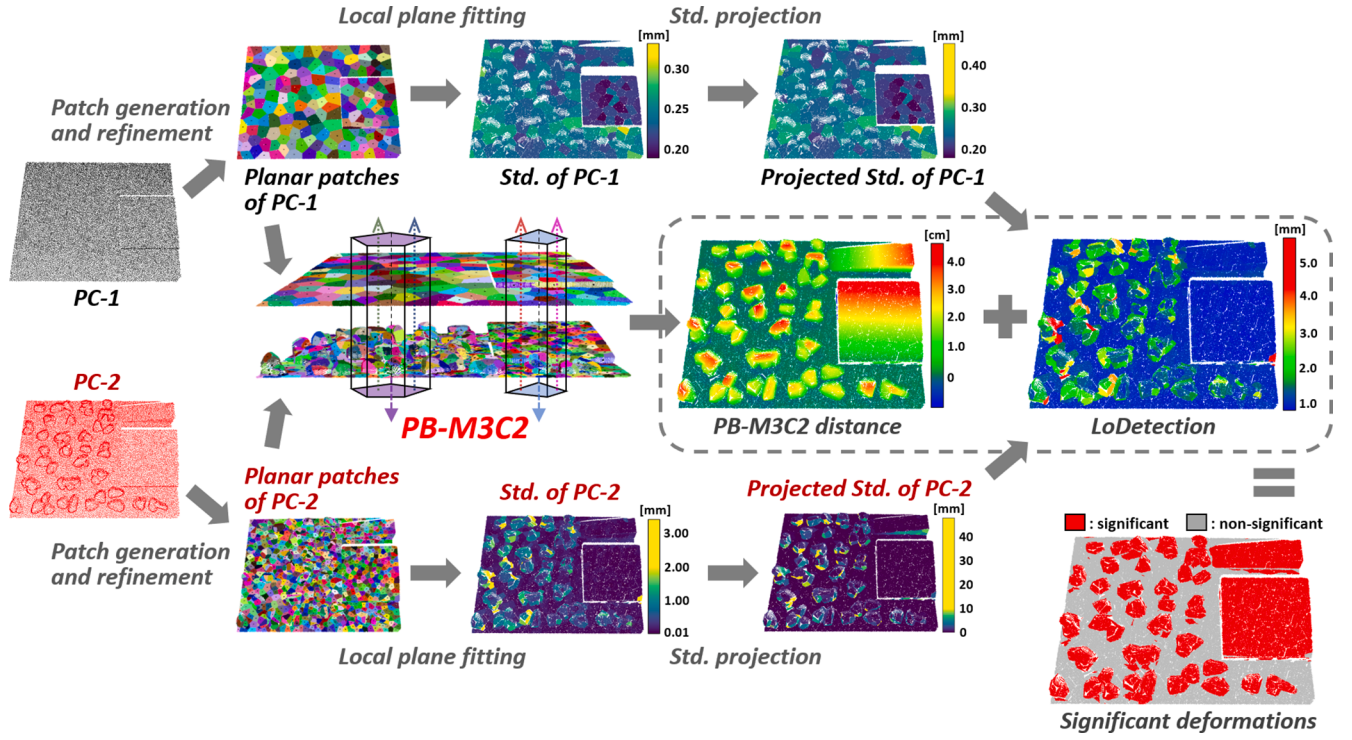


Fig. 1. The workflow of patch-based M3C2 (PB-M3C2).

boundaries of surface discontinuities (Gojic, 2021; Lin et al., 2018). A more detailed description of the supervoxel-based over-segmentation method is beyond the scope of this article, and the interested reader is referred to Lin et al. (2018) and Papon et al. (2013) for more information. The size of supervoxels is capable of adapting to the surface variation of point clouds automatically as long as an appropriate initial size (resolution) of supervoxels is set by the user. Two empirical ways to determine the initial resolution of supervoxels are adopted in this article: (1) Using twenty times (or larger for planar surfaces) the average point spacing of the point cloud to ensure enough points within each patch; (2) Taking the same size (diameter) of the cylinder in standard M3C2 for the following performance comparison. The final size of generated supervoxels may be smaller than the initial resolution in rough areas or larger in smooth areas (Lin et al., 2018).

The additional advantage of introducing supervoxel to laser scanner-based deformation analysis is that the points in one supervoxel are correlated to some degree due to their short spatial distances, subequal incident angles, and similar surface properties. Hence, the spatial correlations in point clouds from the laser scanning process could be considered in the local modeling of these patches.

The simplest model for the generated patches is the best-fitting planes by means of principal component analysis (PCA) or random sample consensus (RANSAC). To approximate the uncertainties of individual points, an empirical standard deviation ($\hat{\sigma}(\text{patch})$) of all points in a patch is defined by the root mean square of the orthogonal distances (Dist) from points in the patch (number of points: n_{patch}) to their best-fitting plane, as denoted in Equation (1). It should be emphasized that the standard deviation defined herein is only an approximation of the measurement uncertainties and is further used for determining the LoDetection.

$$\hat{\sigma}(\text{patch}) = \sqrt{\frac{\sum_{i=1}^{n_{\text{patch}}} \text{Dist}_i^2}{n_{\text{patch}} - 1}} \quad (1)$$

For PCA-based plane fitting, points too far away from the fitted patch plane (e.g., $\text{Dist} > 3\hat{\sigma}(\text{patch})$) could be eliminated to reduce the

influence of imperfect segments (e.g., the points on two planes near the boundary are clustered into one patch). This optional patch refinement procedure sacrifices the non-planar points to achieve better accuracy in patch modeling for surfaces with high roughness and noise. Besides, the patches with too few points (e.g., <10) or too scattered distribution should also be discarded.

2.2. Definition of deformation directions

In defined direction-based methods, the direction of deformation can be flexibly defined according to the prior knowledge (e.g., causes of deformation like gravity) or actual demands for geomonitoring tasks (e.g., the direction of interest like surface normals). Assuming that local patches deform along consistent directions respectively (as depicted in Section 2.1.1), we define or calculate a deformation direction for the entire single patch and impose it on each point within the patch. These deformation directions of all patches can be denoted by a set of direction vectors

$$\vec{N}_{\text{patch} \times 3} = [\mathbf{d}_{\text{patch}_1} \cdots \mathbf{d}_{\text{patch}_i} \cdots \mathbf{d}_{\text{patch}_n}]^T \quad (2)$$

where $\mathbf{d}_{\text{patch}_i} = (d_{x_i}, d_{y_i}, d_{z_i})$ denotes the deformation direction of a patch, and N_{patch} is the number of generated patches. The subsequent calculations of PB-M3C2 distances and associated projected Std. of each patch will be performed along these direction vectors, respectively.

Herein, the definition of deformation directions in PB-M3C2 is generalized and extended from that in standard M3C2, which is specialized to surface normals (Lague et al., 2013). Fig. 2 illustrates three ways to define the deformation direction for each patch in PB-M3C2: Pre-defined consistent direction, multi-scale normal direction, and patch-based normal direction.

2.2.1. Pre-defined consistent direction

The simplest way is to define a specific deformation direction imposed on the entire point cloud for the distance calculation of all points. Some typical ways to define a consistent deformation direction

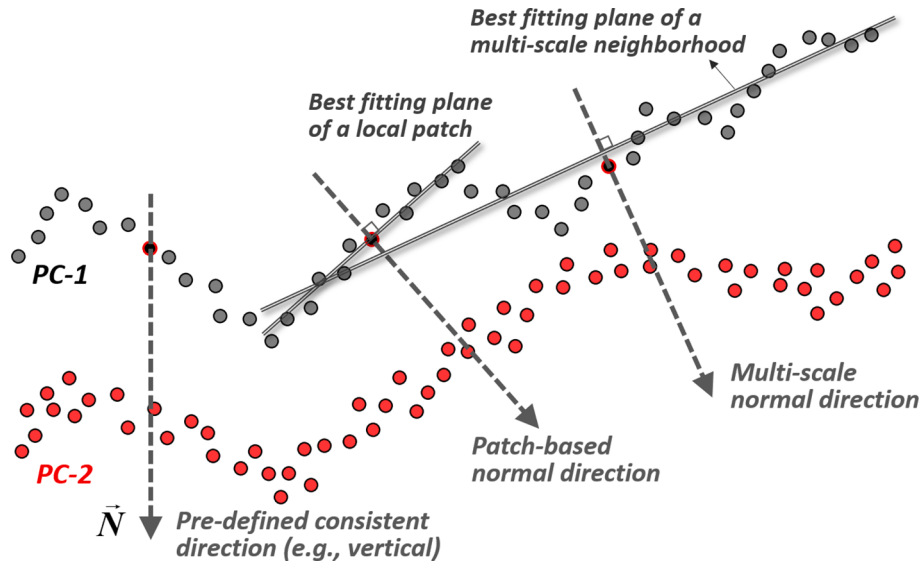


Fig. 2. Three definitions of the deformation direction in PB-M3C2.

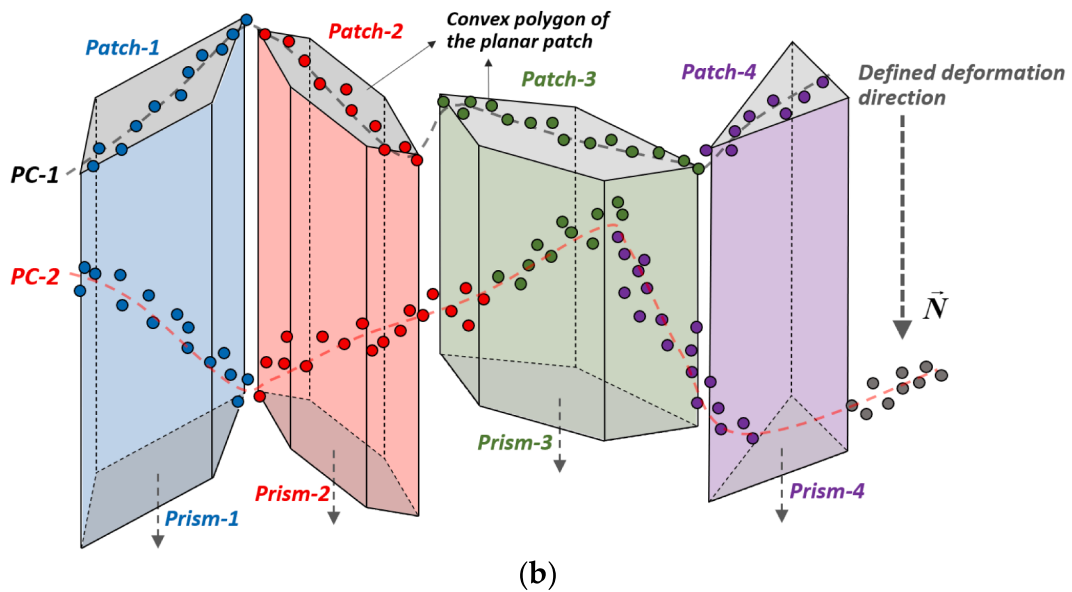
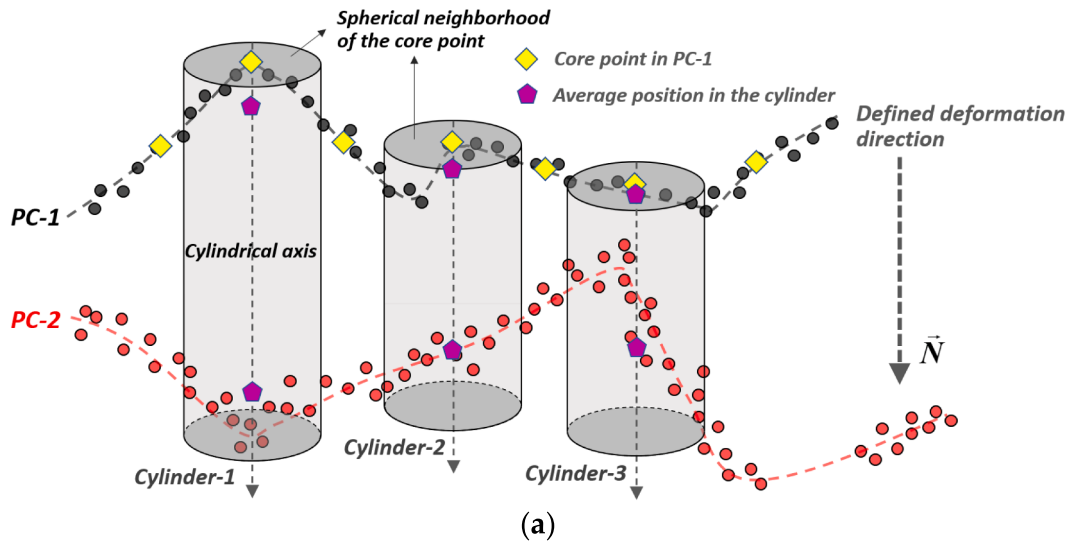


Fig. 3. The construction ways of cylinders in standard M3C2 (a) and prisms in PB-M3C2 (b).

are listed as follows:

- Vertical direction: when gravity is regarded as the cause of deformation, the motion of the monitored object is dominantly along the vertical direction. In this case, the direction vectors will be $(0, 0, 1)$ for all patches;
- Line-of-sight direction: when two-epoch point clouds are acquired by a terrestrial laser scanner (TLS) at the same station, deformations along the ranging direction of the scanner are sensitive to be detected. In this case, the direction vector is along the line between the measured point and the viewpoint (scanner center), and it can be denoted by $(\frac{x_i}{R}, \frac{y_i}{R}, \frac{z_i}{R})$, where (x_i, y_i, z_i) is the coordinate of the original measurement and $R = \sqrt{x_i^2 + y_i^2 + z_i^2}$ is the ranging distance;
- Direction of interest: the user-defined direction considering some prior knowledge of the deformation direction or demands of specific monitoring tasks (e.g., the radial direction of a tunnel for monitoring its convergence).

2.2.2. Multi-scale normal direction

In the workflow of standard M3C2, assumed deformation directions are defined by local surface normals in 3D (Lague et al., 2013). A simple way is to define a fixed scale (radius) or k -nearest neighbors to yield neighboring points that are used for estimating a local surface normal as the orientation of the cylinder for each core point. However, the normal estimation by a fixed scale is not adaptive to the surface with high variation and roughness, leading to a potential overestimation of orthogonal distances between two surfaces. Therefore, a multi-scale normal estimation is proposed in standard M3C2 to prevent surface normal calculations from being affected by noise and roughness: The optimal normal scale is determined by choosing the scale with the smallest curvature over a range of scales defined by the user (Lague et al., 2013).

2.2.3. Patch-based normal direction

The deformation directions defined by multi-scale normal estimation are smoother and more robust against high surface roughness than those by fixed-scale normals, while the computing time is significantly longer for its brute-force curvature computation. Besides, small deformations may be overestimated when the estimated multi-scale normal deviates too much from the actual local surface orientation.

Benefiting from the local planarity of generated patches, we can directly derive local surface normals based on the orientation of each patch by plane fitting. This method is desirable and sensitive for small out-of-plane deformations between two surfaces. In addition, the computational efficiency can be greatly improved owing to the absence of a neighboring-point search for normal estimation.

2.3. Deformation quantification between two point clouds

Similar to standard M3C2, the deformation quantification between two surfaces in PB-M3C2 is achieved by calculating spatial distances along defined deformation directions (Section 2.2). This section elaborates on the main differences between PB-M3C2 and standard M3C2 in distance calculation.

2.3.1. Using prisms instead of the cylinders in M3C2

Fig. 3(a) illustrates that a set of core points is generated by uniformly subsampling PC-1 in standard M3C2. A cylinder is then constructed by extending a spherical neighborhood of the core point to capture the local neighbors of two point clouds. The cylindrical axis goes through each core point and is oriented to the defined normal direction. The distance between the average positions of two neighborhoods within the cylinder is regarded as the deformation value at the core point. Compared to C2C and C2M, the way of averaging local neighbors from the cylinder can effectively weaken the influence of measurement noise on the distance

calculation, and the estimated local roughness allows a statistical significance test for the deformation. Besides, the distances between non-overlapping areas will not be calculated, as the related cylinder captures insufficient points.

However, the cylinder will be highly overlapping when sampling high-resolution core points, resulting in an over-smoothing effect of calculated distances. For the areas with non-planar, discontinuous, or sharp structures (i.e., high roughness), the average position in the cylinder may deviate from the actual surface, leading to an incorrect deformation quantification. In addition, the empirical standard deviation approximated by local surface roughness is potentially overestimated, because the actual surface variation and measurement uncertainties are confused by the cylinder.

To solve the above limitations in standard M3C2, the proposed PB-M3C2 utilizes segmented planar patches to separate measurement uncertainties and real surface variations. In this case, cylinders with a constant scale are no longer suitable to capture the corresponding neighbors in the other point cloud due to the irregular shapes of generated planar patches (supervoxels). As shown in Fig. 3(b), in PB-M3C2, we generate polygons based on the constructed convex hulls of planar patches from PC-1. Then we construct a prism by extending the polygon along the defined deformation direction. Similar to the construction method of the cylinder in M3C2, the prism extends progressively towards PC-2 from the associated patch in PC-1. In PB-M3C2, we extend the prism in alternating directions until it incorporates the PC-2 surface, ensuring that only the closest area of PC-2 is captured. The maximum length of the prism should be set by the user to avoid endless extension by considering the assumed maximum deformation magnitude.

The construction process of polygons of generated patches is presented in Fig. 4: We first project measured points on the best-fitting plane of the corresponding patch, then we construct a 2D convex hull based on the projected points as a convex polygon that will be extended to form a prism. We perform this process on each patch. Hence gaps or overlaps may arise between these polygons, and inconsistent deformation calculations potentially exist at the same position in these overlapping areas. This issue will be discussed in Section 4.2.

2.3.2. Projecting standard deviations along defined deformation directions and projecting points onto local patch planes

In standard M3C2, two subsets of points are intercepted by the defined cylinder of radius $d/2$ (d is called projection scale) and then projected onto the cylindrical axis, yielding two distributions on the axis. The means and standard deviations of the distributions will be respectively used as the average positions and local roughness ($\hat{\sigma}_1(d)$ and $\hat{\sigma}_2(d)$) of these two subsets of points. The distance between two average positions is calculated as the deformation magnitude at the associated core point (i.e., M3C2 distance), as shown in Fig. 5(a).

In PB-M3C2, all points in the patch are first projected onto a locally fitted patch plane. As defined in Equation (1), we use the standard deviation ($\hat{\sigma}(patch)$) from plane fitting to approximate the local uncertainties for each patch ($\hat{\sigma}_1(patch.i)$ and $\hat{\sigma}_2(patch.j)$) instead of the local roughness employed in standard M3C2, as shown in Fig. 5(b). Since these standard deviations only reflect the uncertainties in the direction of respective patch normals, we project them along the defined deformation directions for the following calculation of LoDetection. The projected standard deviations ($\hat{\sigma}'(patch)$) can be derived by

$$\hat{\sigma}'(patch) = \frac{\hat{\sigma}(patch)}{|\cos\langle \mathbf{n}_{patch}, \mathbf{d}_{patch} \rangle|} \quad (3)$$

where $\mathbf{n}_{patch}$ and $\mathbf{d}_{patch}$ are the normal vector of the patch and the defined deformation direction imposed on this patch (see Equation (2)), respectively. Particularly when using the patch-based normal direction as the deformation direction of each patch (i.e., the angle $\theta =$

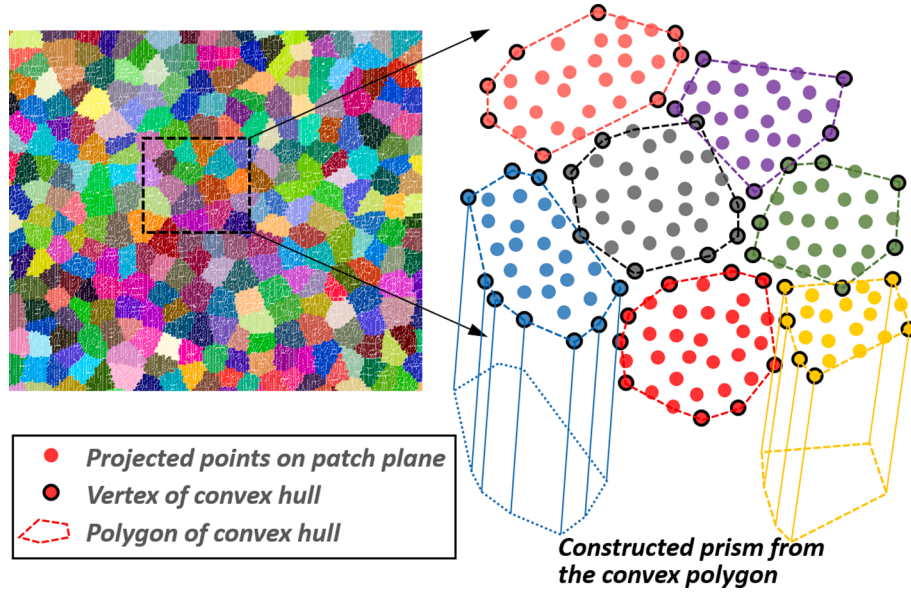


Fig. 4. The construction of convex polygons of segmented patches.

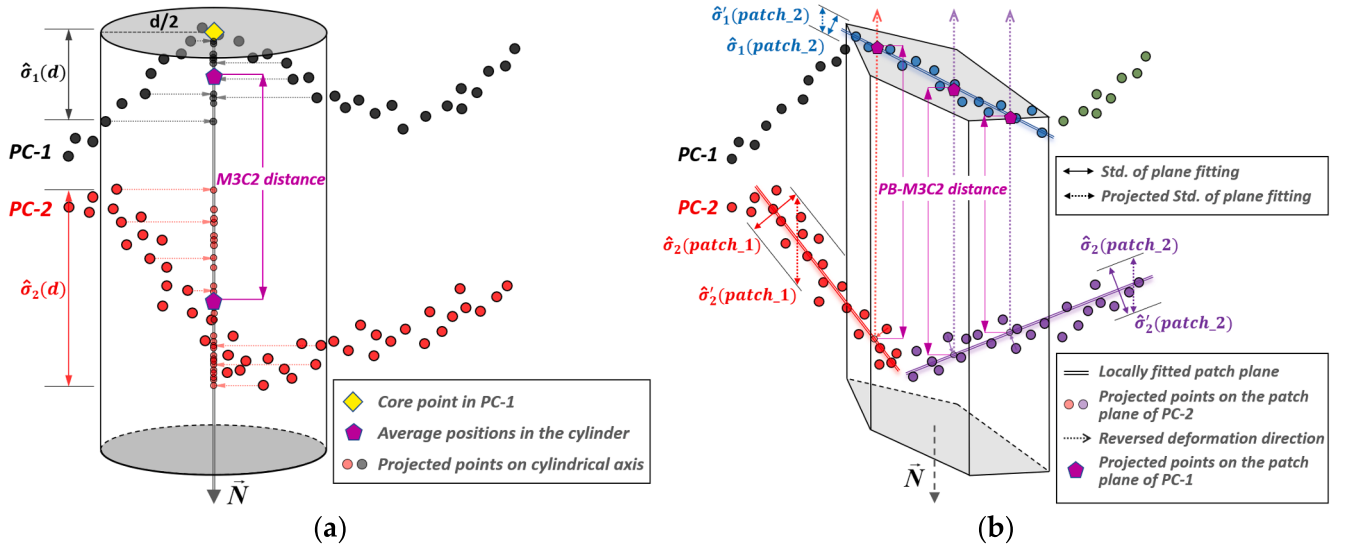


Fig. 5. The distance calculation between two surfaces by standard M3C2 (a) and PB-M3C2 (b).

$\arccos\left(\frac{n_{patch} \cdot d_{patch}}{|n_{patch}| |d_{patch}|}\right)$ between d_{patch} and n_{patch} is 0° or 180°), $\hat{\sigma}'(patch) = \hat{\sigma}(patch)$. When θ is close to 90° , $\hat{\sigma}'(patch)$ will become extremely large (increasing in multiples of $\cos^{-1}\theta$) and the deformations are nearly in-plane movements that PB-M3C2 cannot detect. Thereby, we only calculate deformations for patches with $\theta \leq 88^\circ$ empirically in PB-M3C2 ($\hat{\sigma}'(patch) \approx 30\hat{\sigma}(patch)$ when $\theta = 88^\circ$). The way of estimating the *Std.* and projected *Std.* for all points within a patch exactly corresponds to the local consistency assumption for measurement uncertainties in Section 2.1.1.

As the projected points captured by the prism in PC-2 may be located on different patch planes, we first use these projected points as average positions of PC-2, and further project them onto the corresponding patch plane in PC-1 along the reversed defined deformation direction. As shown in Fig. 5(b), we calculate the distance between two corresponding projected points within the prism as the deformation magnitude at the associated projected point (i.e., *PB-M3C2 distance*). Again, the way of projecting the points in PC-2 captured by the prism onto the patch plane

in PC-1 to calculate surface distances exactly corresponds to the local consistency assumption of deformation directions in Section 2.1.1. Since the actual surface variations are separated by generated planar patches, the projected points used for distance calculation are closer to the real surface, which is free from the influence of surface variability. Furthermore, the resolution of derived deformations will keep in line with the resolution of the original PC-2 owing to the projection of original measurements instead of the subsampled core points in standard M3C2, and resampling on the modeled patch planes could further improve the resolution of deformation analysis.

2.4. Level of detection with lower uncertainty

In standard M3C2, the local roughness ($\hat{\sigma}_1(d)$ and $\hat{\sigma}_2(d)$) and number of points (n_1 and n_2) within the cylinder are used to estimate local uncertainties with respect to the calculated deformation (*M3C2 distance*). Based on a statistical *t*-test and the assumption of Gaussian distributed errors, a spatially variable confidence interval at a specified confidence level of *P* is defined as the LoDetection by Equation (4), incorporating an

average registration uncertainty $\hat{\sigma}_{reg}$. t_p is the quantile of a two-tailed t -distribution at the confidence level P with the degrees of freedom $f = n_1 + n_2 - 2$ (e.g., $t_p = 1.98$ when $P = 95\%$ and $f = 100$).

$$LoDetection_P(d) = \pm t_p \left(\sqrt{\frac{\hat{\sigma}_1(d)^2}{n_1} + \frac{\hat{\sigma}_2(d)^2}{n_2}} + \hat{\sigma}_{reg} \right) \quad (4)$$

However, the estimated local roughness from standard M3C2 is comprised of not only measurement uncertainties but also the variation of real surface geometries. The latter (local surfaces that are non-planar or non-perpendicular to the cylinder's axis) will lead to a higher $\hat{\sigma}(d)$, thus increasing the $LoDetection$ derived from Equation (4). The trade-off between accurate local average and low roughness by selecting the optimal projection scale d in M3C2 has been investigated by Lague et al. (2013) and DiFrancesco et al. (2020), while an adaptive cylinder scale is still challenging for surfaces with complex geometries and high roughness.

To decrease the uncertainties of calculated distances, we employ the standard deviations from patch plane fitting and project them along associated deformation directions, thus deriving a more realistic $LoDetection$ in PB-M3C2 as

$$LoDetection_P(patch_i) = \pm t_p \left(\sqrt{\frac{\hat{\sigma}'_1(patch_i)^2}{n'_1} + \frac{\hat{\sigma}'_2(patch_i)^2}{n'_2}} + \hat{\sigma}_{reg} \right) \quad (5)$$

where $\hat{\sigma}'_1(patch_i)$ and $\hat{\sigma}'_2(patch_i)$ are the projected standard deviations (calculated by Equation (3)) of associated patches in PC-1 and PC-2 respectively, n'_1 and n'_2 are the respective number of points in each patch, and t_p is the quantile with the degrees of freedom $f' = n'_1 + n'_2 - 2$. Deformations that are larger than $LoDetection$ are regarded as significant.

If the correlation between the points within one patch (supervoxel) (as explained in Section 2.1.2) is considered in the patch modeling, n' in Equation (5) should be replaced by the effective number of

measurements n_{eff} which is defined as (Schmitz et al., 2020)

$$n_{eff} = \frac{n'}{1 + 2 \cdot \sum_{i=1}^{n'-1} \left(\frac{n'-i}{n'} \cdot K(i) \right)} \quad (6)$$

where $K(i)$ describes the correlation coefficient between two measurements in a patch.

To simplify the computation of n_{eff} , we adopt a constant empirical value of spatial correlations K for TLS point clouds to replace $K(i)$, resulting in a simplified n'_{eff} as

$$n'_{eff} = \frac{n'}{1 + K \cdot (n' - 1)} \quad (7)$$

If no correlation is assumed in the point cloud, the effective number of measurements equals the number of all points involved in the plane fitting. Obviously, the higher the correlation between points in a patch, the less the effective number of measurements, leading to a higher $LoDetection$.

3. Experimental evaluation

We use three datasets to verify and evaluate the proposed PB-M3C2 algorithm: (1) Synthetic point clouds with defined geometries, noise, and deformations; (2) Two-epoch scans of an indoor scene with simulated changes (short scanning distance); (3) One scan of a rock cliff façade with defined deformations (long scanning distance), complemented by a simulated scan representing the second epoch. The deformation analysis results by PB-M3C2 are systematically evaluated and compared with the standard M3C2 algorithm.

3.1. Synthetic point clouds

In this experiment, we generate two-epoch synthetic point cloud surfaces numerically, which are composed of small planes with specifically defined geometries and independent Gaussian noise (standard

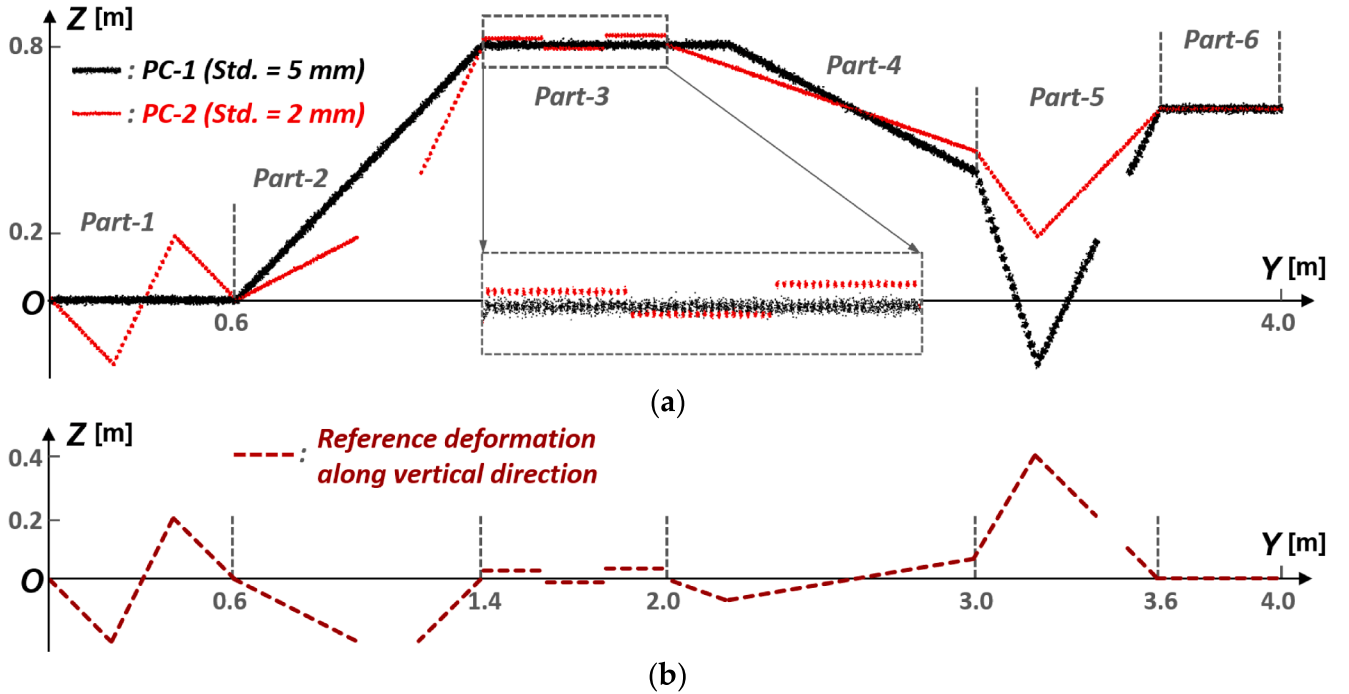


Fig. 6. Synthetic two-epoch point clouds and related reference deformation (front view): (a) Two surfaces with defined deformations along the vertical direction (Part-1 contains sharp structures in PC-2; Part-2 includes a non-overlapping area in PC-2; Part-3 consists of three deformed planes with small vertical movements of +2 cm, −1 cm, and +3 cm; Part-4 represents gradual deformations by two intersecting planes; Part-5 contains a non-overlapping area in PC-1 and different sharp structures in both clouds; No deformation occurs in Part-6); (b) The reference deformation magnitudes along the vertical direction are derived from plane equations.

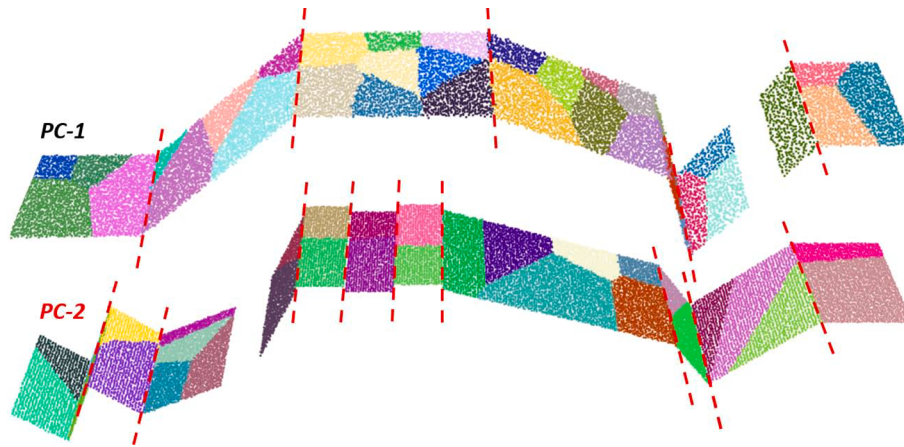


Fig. 7. Generated patches by supervoxel-based segmentation (boundaries of planes are highlighted by red dashed lines). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

deviations are 5 mm and 2 mm for PC-1 and PC-2, respectively). As shown in Fig. 6, five parts are constructed along the Y-axis to simulate different surface changes. Both surfaces are 0.5 m in width and 4 m in length, with an average point spacing of 1 cm in the horizontal direction. Since the reference deformation (ground truth) can be derived by calculating the distances between two corresponding planes from their equations, we can evaluate the absolute accuracy of quantified deformations. For the comparison with standard M3C2 under the same configurations, we define the deformation direction as uniformly vertical (along the Z-axis) for both methods. Hence the reference deformations are calculated along the vertical direction as well.

Fig. 7 presents the generated patches of two point clouds with good boundary separation by a better boundary preservation supervoxel segmentation method (Lin et al., 2018). The size of supervoxels is initially set as 30 times the average point spacing. After the segmentation process, however, they can adapt to the surface variations, leading to irregular shapes and distributions.

Two diameters of cylinders ($d = 10$ cm and $d = 20$ cm) are used in the standard M3C2. Considering the advantages of M3C2 (depicted in Section 1.2), we compare the performance of PB-M3C2 solely with standard M3C2 in this dataset. Fig. 8 gives the calculated vertical distances between two surfaces and associated absolute accuracy of two algorithms (all results are displayed on PC-1). Generally, PB-M3C2 exhibits better accuracy than standard M3C2, particularly in areas with discontinuous boundaries and sharp structures (see Part-1 ~ 3 and Part-5).

It can be seen that in standard M3C2 a small cylinder enables an improvement in the distance accuracy near discontinuous areas but may yield noise in distance calculation (see Part-1) due to insufficient points in the cylinder. Nevertheless, a larger cylinder diameter can cause incorrect over-smooth deformations (see the discontinuous boundaries in Part-3 in Fig. 8(a)). Besides, the non-overlapping area in Part-2 is incorrectly involved in the distance calculation under a larger cylinder diameter. In contrast, these areas in PB-M3C2 are well preserved as the regions where deformations cannot be calculated, for these areas are not measured in both epochs.

Fig. 9 shows the empirical uncertainties (i.e., *Std.* from local modeling and their projection along the vertical direction in PB-M3C2) of two-epoch point clouds estimated by two methods. The discontinuous and rough areas show higher uncertainties than planar areas in standard M3C2, and a larger diameter of the cylinder may yield higher and inconsistent uncertainties near the rough areas (see Fig. 9(a) and (b)). The uncertainties estimated by PB-M3C2 are generally much lower than that by standard M3C2, and basically agree with the defined Gaussian noise of respective point clouds (see Fig. 9(c) and (d)). The slight difference in *Std.* between these patches in Fig. 9(c) is mainly caused by their imperfect segmentation, while the variation of projected *Std.* in

Fig. 9(d) is due to the varying angles between the deformation direction (vertical in this case) and respective patch normals.

Due to the independently distributed Gaussian noise imposed on each point, there is no correlation within the patch (i.e., $K = 0$). Thus, significant deformations, as shown in Fig. 10, are detected by comparing to the LoDetection (at a significance level of 5 %) estimated by Equation (4) and Equation (5) in standard M3C2 and PB-M3C2, respectively. The reference of significant deformations is also given to evaluate the results of significance test from two methods. Again, with lower uncertainties, the test result of PB-M3C2 agrees better with the reference, even for the small deformations near the rough and discontinuous areas (in Part-3).

3.2. Indoor scene

As depicted in Fig. 11, we simulate an indoor scene with manually changed and deformed objects arranged on the ground. Leica HDS7000 laser scanner is used to capture the investigated area in two epochs. The first scan only incorporates two flat wooden boards, while the second represents a deformed surface with complex geometries and high roughness. This specific design could qualitatively evaluate the derived deformations by comparing the visualized deformation magnitudes to the surface geometry of PC-2. Although it is difficult to obtain the actual deformation magnitude of each point (e.g., vertical distances between two surfaces), this indoor experiment establishes a highly controlled situation where the stable and deformed parts are known, which can be used as the reference to evaluate the significance of quantified deformations.

The deformation direction in this dataset is again defined as vertical for comparison purposes. For clarity, we display quantified deformations and associated uncertainties on PC-2, as presented in Fig. 12. Since noisy distance quantifications or over-smoothing effects may arise with a too-small or too-large cylinder scale, we set $d = 3$ cm (the same as the initial size of supervoxels set in PB-M3C2) and $d = 2$ cm as trade-offs in standard M3C2. The calculated vertical distances near gravels' boundaries are underestimated by standard M3C2 (see Fig. 12(a)) due to its average effect by the cylinder in rough areas, whereas the uncertainties are overestimated near these areas by both cylinder scales (see Fig. 12(b)). In PB-M3C2, derived deformations are more consistent with the surface variations of PC-2 (see Fig. 12(a)), and estimated uncertainties are more uniform and much smaller than that estimated by standard M3C2 except some steep areas of gravels with higher projected *Std.* (see Fig. 12(b)).

The detected significant deformations (at a significance level of 5 %) and the reference by manually classifying the stable and deformed parts are presented in Fig. 13. Since the very short spatial distance (1.5 mm on average) and locally consistent material between neighboring points,

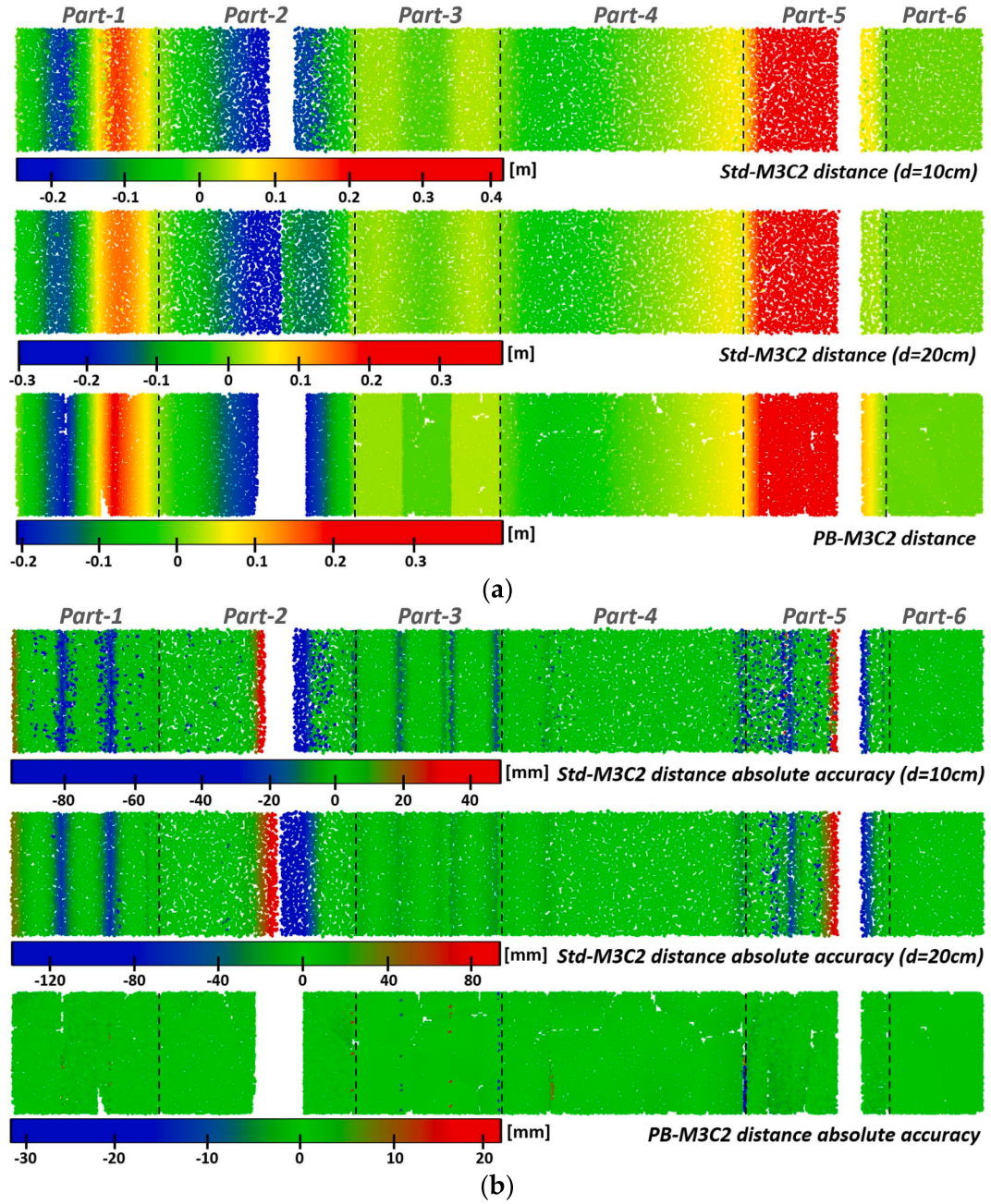


Fig. 8. The quantified deformations by standard M3C2 (Std-M3C2) and PB-M3C2 and their absolute accuracy: (a) Calculated distances between two-epoch point clouds; (b) Absolute accuracy of quantified deformations by comparing with the reference.

high spatial correlation probably exists within each patch. Hence, we determine the LoDetection for each patch by Equation (5) and Equation (7) in PB-M3C2, using a constant correlation coefficient (K). In addition, an average registration uncertainty ($\hat{\sigma}_{reg} = 0.3$ mm) estimated from a target-based registration procedure is employed in calculating the LoDetection for both methods.

For standard M3C2, boundaries between detected significant and non-significant areas are either over-smoothed (when $d = 3$ cm) or indistinguishable (when $d = 2$ cm), especially around the edges of gravels (see Fig. 13(a) and (b)). This inconsistency with the gravel's contour is caused by the underestimated deformations and over-estimated uncertainties in these areas. For PB-M3C2, some stable areas are incorrectly classified as significantly deformed without considering measurement correlations (see Fig. 13(c)), while the distribution of significant deformations is closer to the reference (see Fig. 13(d)) by

adopting an empirical correlation coefficient of 0.65 from Kauker and Schwieger (2017). However, some steep areas can still not be detected as significant due to the overestimated projected Std. compared to their realistic uncertainties.

3.3. Façade of a rock cliff

To verify the applicability of PB-M3C2 on 3D point clouds at different scales, we use the TLS point cloud of a selected rock cliff façade to evaluate the algorithms' performance in natural scenes (Hassan et al., 2022). The rock cliff surface with high variation and roughness is shown in Fig. 14. Since no significant deformations occurred over monitoring epochs, we generate the second-epoch surface by defining a certain translation of the whole surface oriented to its normal to simulate small deformations on complex topographies. This translation direction is

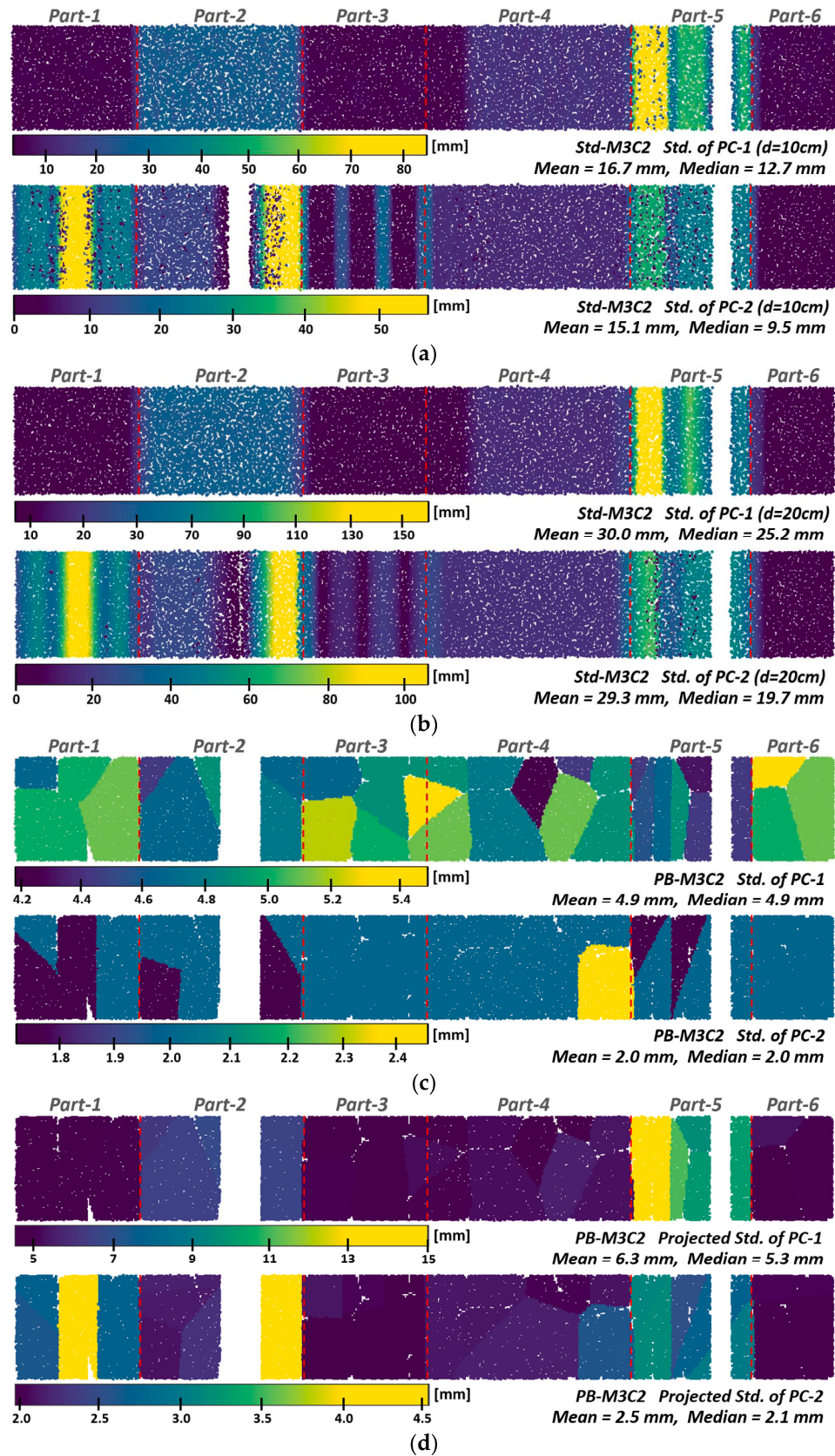


Fig. 9. Estimated standard deviations of two point clouds by standard M3C2 (a, b) and PB-M3C2 (c, d).

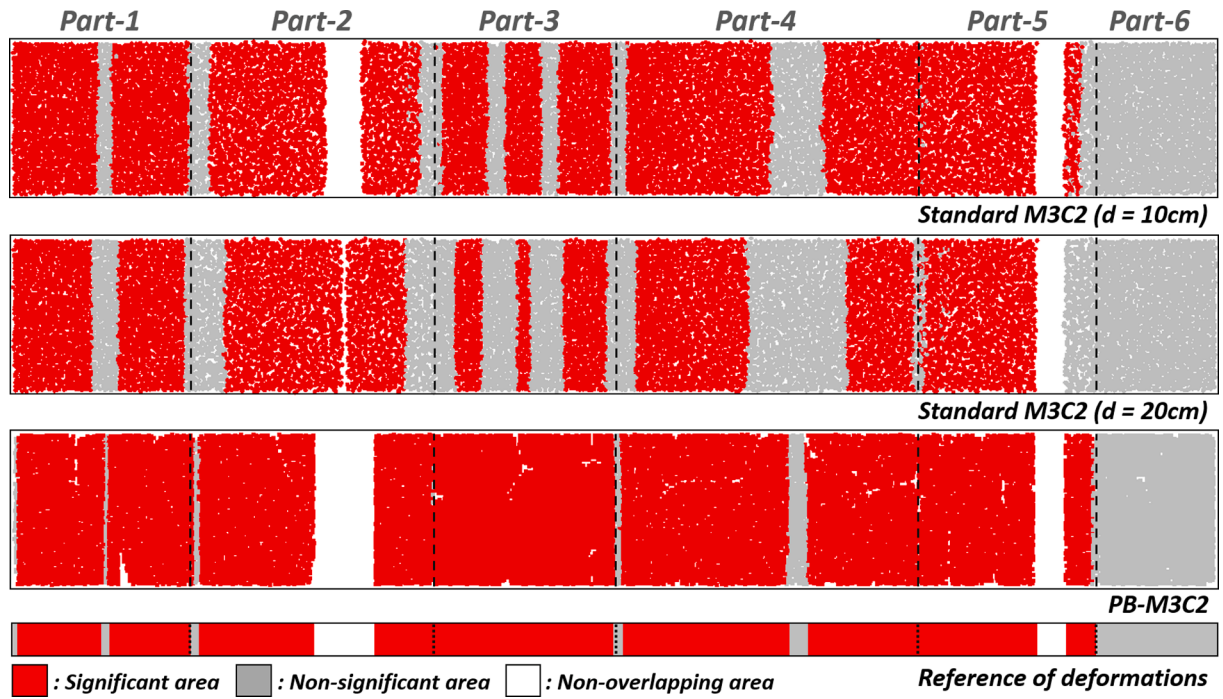


Fig. 10. The significance test ($P = 95\%$) of quantified deformations in dataset 1.

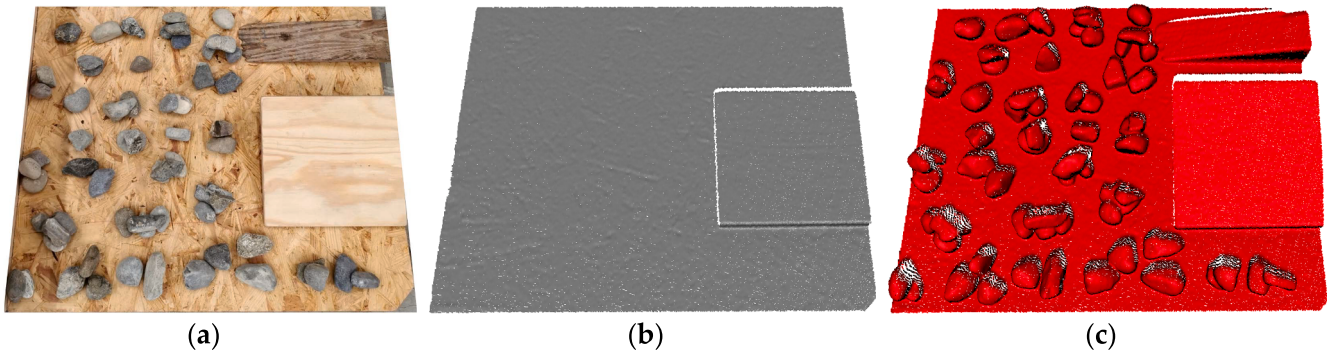


Fig. 11. Experimental setup of the indoor scene: (a) shows the artificial changes and deformations by placing irregular objects (gravels and a wedged wood block) on the ground and lifting a wooden board on one side; (b) and (c) are captured point clouds in epoch 1 (PC-1) and epoch 2 (PC-2) respectively.

taken as the defined deformation direction in this dataset for both standard M3C2 and PB-M3C2. We use the defined translation magnitude as the reference to evaluate the absolute accuracy of quantified deformations. It should be noted that some overhanging areas exist in the selected rock cliff façade, and approx. 8 % generated patches from these areas are nearly parallel to the defined translation direction (i.e., $\theta > 88^\circ$). These areas (approx. 8 % of the selected façade) are not considered in the following calculation for both methods, as explained in Section 2.3.2.

As shown in Fig. 15, the estimated uncertainties (*Std.* and projected *Std.*) and associated LoDetection by both methods are presented in two histograms. The distribution of *Std.* by PB-M3C2 is concentrated near the mean of 13 mm, potentially indicating the intrinsic random measurement noise. The mean and median of projected *Std.* are slightly higher than the *Std.* from patch plane fitting but still concentrated and much smaller than the *Std.* by standard M3C2 (see Fig. 15(a)). The associated LoDetection of two methods shown in Fig. 15(b) directly tell the ratio of significant deformations among calculated distances. For example, if the defined translation (i.e., simulated deformation) is 3 cm, almost all quantified deformations will be tested as significant by PB-M3C2 (larger than nearly all LoDetection). Using standard M3C2, however, the areas

with a LoDetection larger than 3 cm are erroneously regarded as non-significantly deformed.

The visualized spatial distributions of LoDetection are depicted in Fig. 16(a). It can be seen that the highly rough areas display much higher LoDetection in standard M3C2, and thus small deformations are unable to be detected in these regions. In contrast, PB-M3C2 shows a more random spatial distribution of LoDetection, and the variation of surface topographies has a minor influence on it, except for some overhanging areas that are almost parallel to the translation direction.

Fig. 16(b) presents the statistical significance of quantified deformations by both methods, where a 3 cm translation is simulated to generate the second-epoch scan. PB-M3C2 has significantly detected 98.5 % deformations on the surface. However, 21.5 % of deformations near the highly rough areas are incorrectly tested as non-significant by standard M3C2. This result exactly verifies the inference based on the histogram of LoDetection demonstrated in Fig. 15(b).

To evaluate the absolute accuracy of deformations quantified by traditional approaches (C2C, C2M and standard M3C2) and PB-M3C2, we simulate the deformations of three different magnitudes (3 cm, 6 cm, and 10 cm) by simple surface translations, including the case of no deformation (0 cm). Then the distributions of detected deformations are

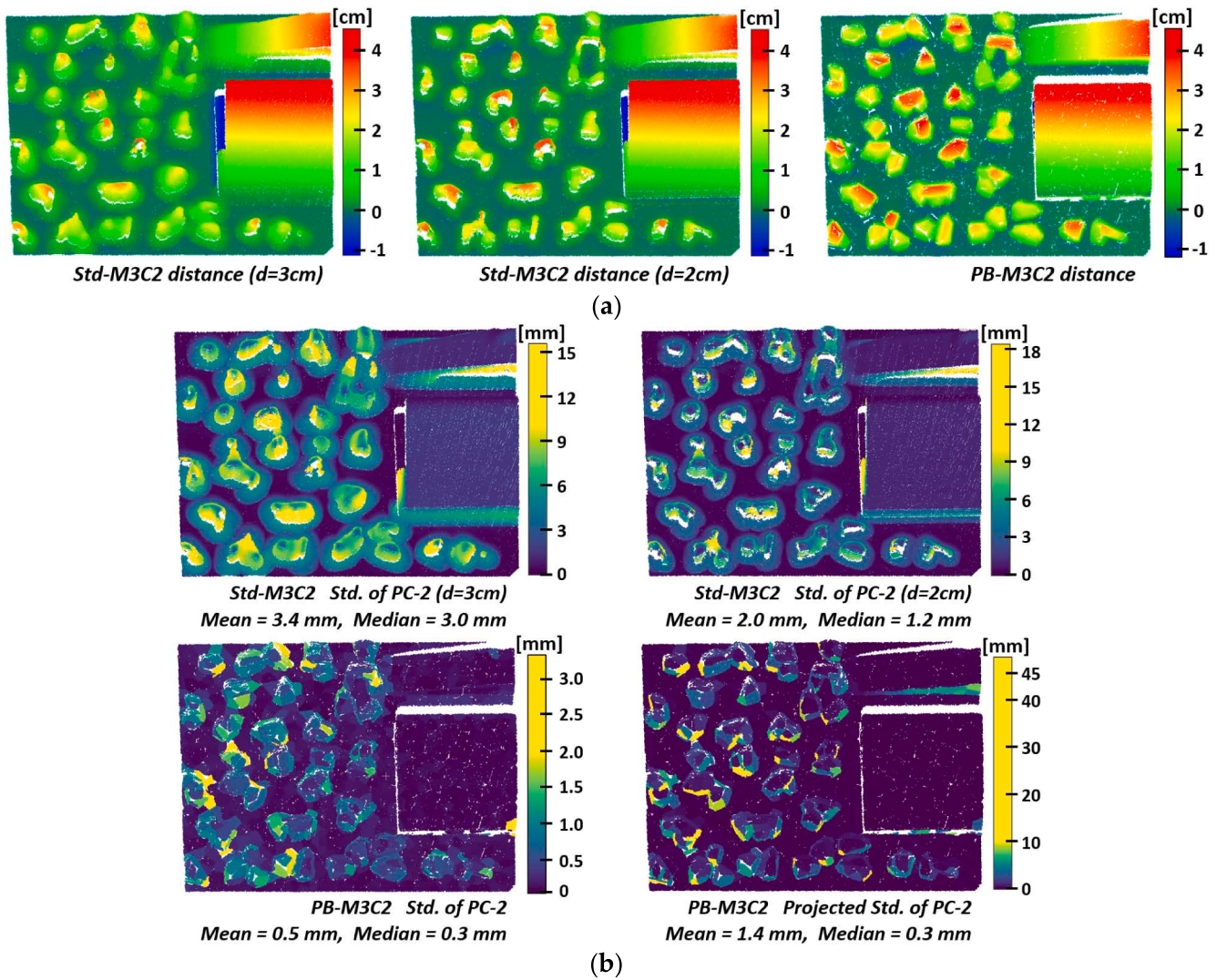


Fig. 12. The quantified deformations (a) and estimated standard deviations of PC-2 (b) by standard M3C2 (Std-M3C2) and PB-M3C2.

analyzed. To simulate the differences in laser scans between two epochs, we subsample the second-epoch point cloud and impose two levels of additional Gaussian noise (with standard deviations of 5 mm and 10 mm) on each measurement.

To quantitatively evaluate the proximity between the calculated deformations and the translation value (as the reference), herein we only calculate the percentage of deformations falling within a specific interval (± 5 mm and ± 10 mm are chosen respectively, considering the imposed Gaussian noise) near the reference. As shown in Fig. 17, when no deformation occurs, C2C shows the worst results due to the influences of measurement noise and point spacing. C2M overcomes the impact of non-uniform point spacing but is still sensitive to measurement uncertainties. Standard M3C2 and PB-M3C2 show much higher ratios of correct deformation detections (i.e., no deformation), even though both methods have not completely eliminated the influence of imposed noise. When we increase the magnitude of simulated deformation, the distribution of detected deformations by PB-M3C2 is closest to the reference compared to the other three methods (more than 95 % of derived deformations are within the specified interval in all cases). The second-best result is from standard M3C2. Since C2C and C2M employ the nearest correspondence for distance calculation without considering the deformation direction, the derived deformations are generally smaller. Compared to C2M, slightly more deformations detected by C2C are actually caused by the inconsistent point spacing in two point clouds

(mistakenly quantified as deformations). In contrast, C2M can overcome the influence of point spacing by using the point-to-mesh distance, so the detected deformations are smaller than C2C for the point clouds with larger point spacing.

4. Discussion

4.1. Comparison with CD-PB M3C2

Since both PB-M3C2 and CD-PB M3C2 utilize segmented planar areas to reduce the uncertainties of distance quantifications and further achieve a lower LoDetection for detecting small deformations, this section compares the main differences and applicable scopes between the two methods as following aspects:

(1) Algorithm function: PB-M3C2 is designed to quantify spatial distances along defined directions between two point cloud surfaces and thus cannot detect in-plane movements, while CD-PB M3C2 can derive real displacements between corresponding planes.

(2) Deformation direction: PB-M3C2 has flexible definitions of deformation directions that allow for considering deformation causes and demands of monitoring tasks. CD-PB M3C2 computes distances merely between corresponding planes along planes' normals.

(3) Spatial resolution: Since the generated planar patches (super-voxels) could cover the entire point cloud, PB-M3C2 enables

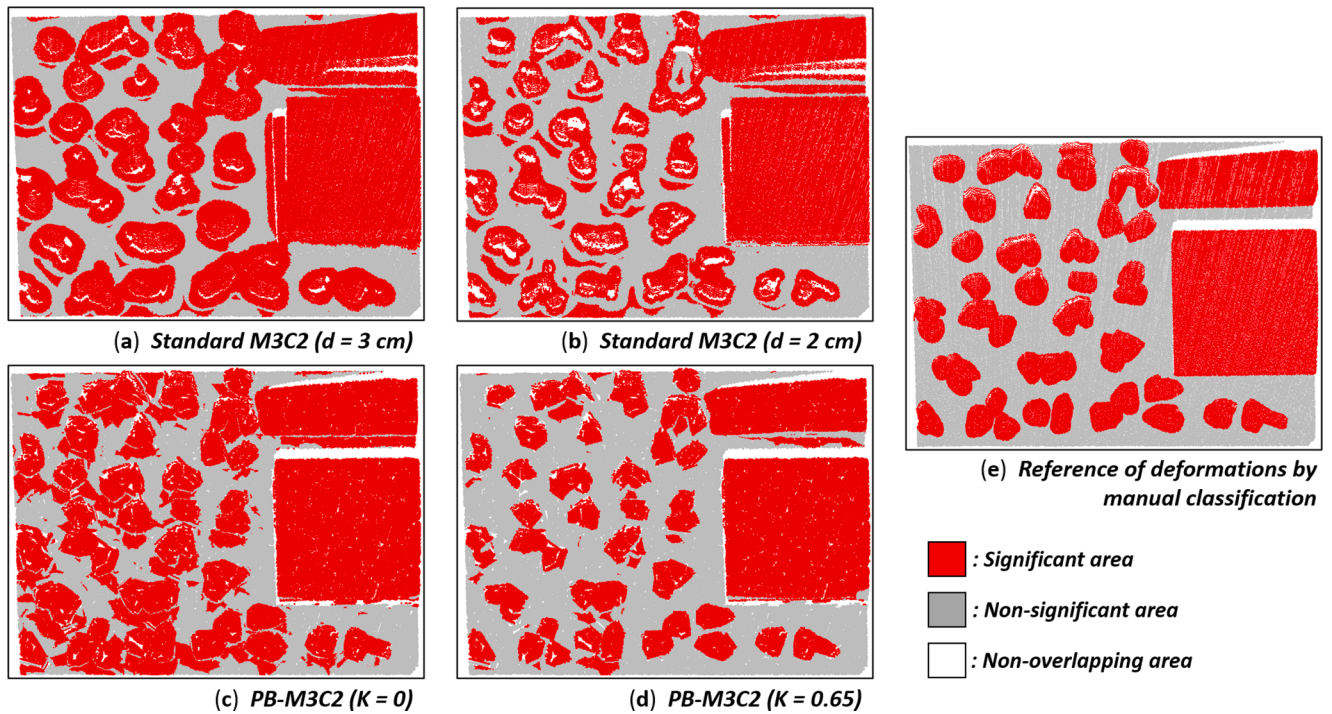


Fig. 13. The significance test ($P = 95\%$) of quantified deformations in dataset 2.

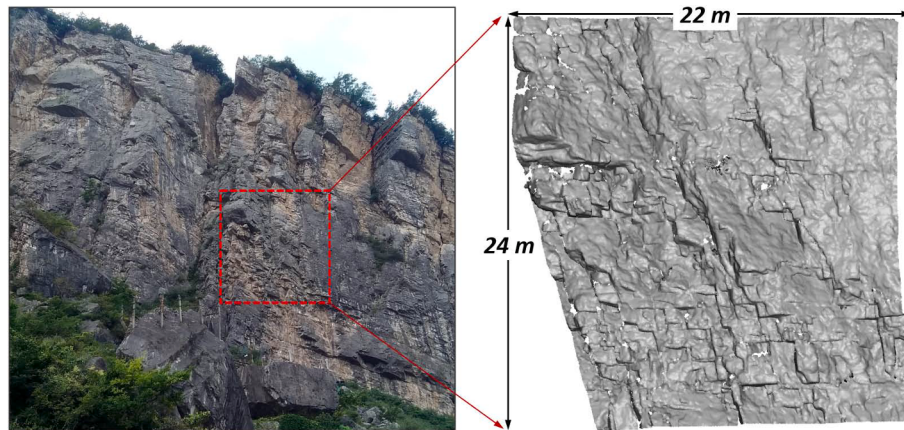


Fig. 14. The scale and surface geometry of the selected rock cliff façade.

deformation (distance) quantification for all overlapping areas between epochs, even for highly deformed areas. However, CD-PB M3C2 is developed to derive deformations (displacements) on extracted identical planes solely from rigid areas.

(4) LoDetection calculation: CD-PB M3C2 employs the standard deviation from plane fitting to calculate LoDetection, thus restricting the deformation analysis merely along planes' normals. PB-M3C2 projects the standard deviations along defined deformation directions, enabling the significance test in more directions. Besides, measurement correlations within planar patches are partially considered to derive a more realistic LoDetection.

4.2. Influence of the patch quality on deformation analysis

The quality of generated patches plays a significant role in PB-M3C2, including the correctness of boundary preservation, patch shapes, etc. Due to the surface variation and measurement noise, the shapes of generated patches may be inhomogeneous, or the boundaries are not

completely separated in a patch (i.e., imperfect segmentation), especially at the boundaries with small curvatures or indistinct discontinuities. These segments may cause a difference in estimated uncertainties between patches, even though the standard deviations of these points are the same, as shown in Fig. 9(c). Therefore, good-quality patches should exclude discontinuities and keep similar shapes.

The prism constructed based on a convex hull requires the shape of the generated patch to approximate a convex polygon. Otherwise, overlaps may arise between adjacent polygons and associated prism spaces, potentially leading to inconsistent deformation values calculated in the overlapping areas of adjacent convex polygons (see Fig. 4). Compared to other supervoxel-based segmentation algorithms, the patches generated by the methods using a merge-swap optimization framework (Lin et al., 2018; Xiao et al., 2020) basically show a shape pattern of a convex polygon.

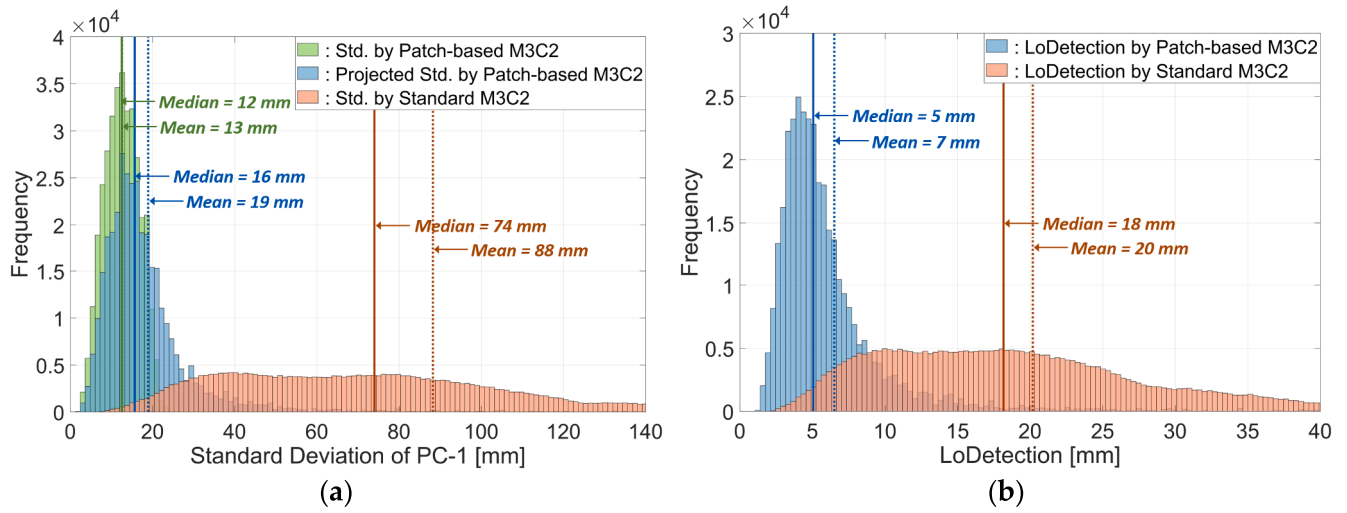


Fig. 15. The histograms of standard deviations (a) and LoDetection (b) by standard M3C2 and PB-M3C2.

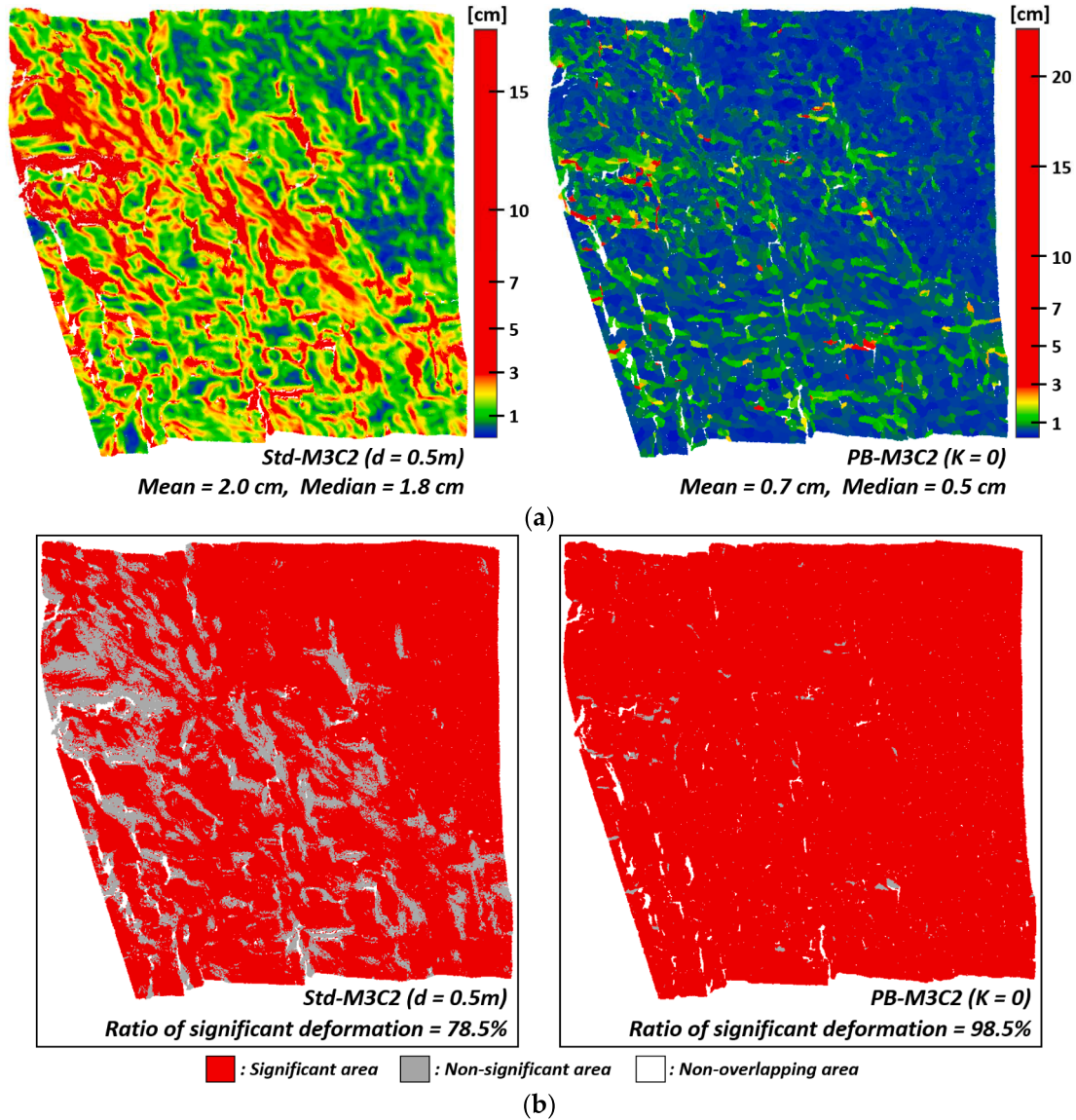


Fig. 16. Spatial distributions of LoDetection (a) and the significance test ($P = 95\%$) of quantified deformations (b) in dataset 3.

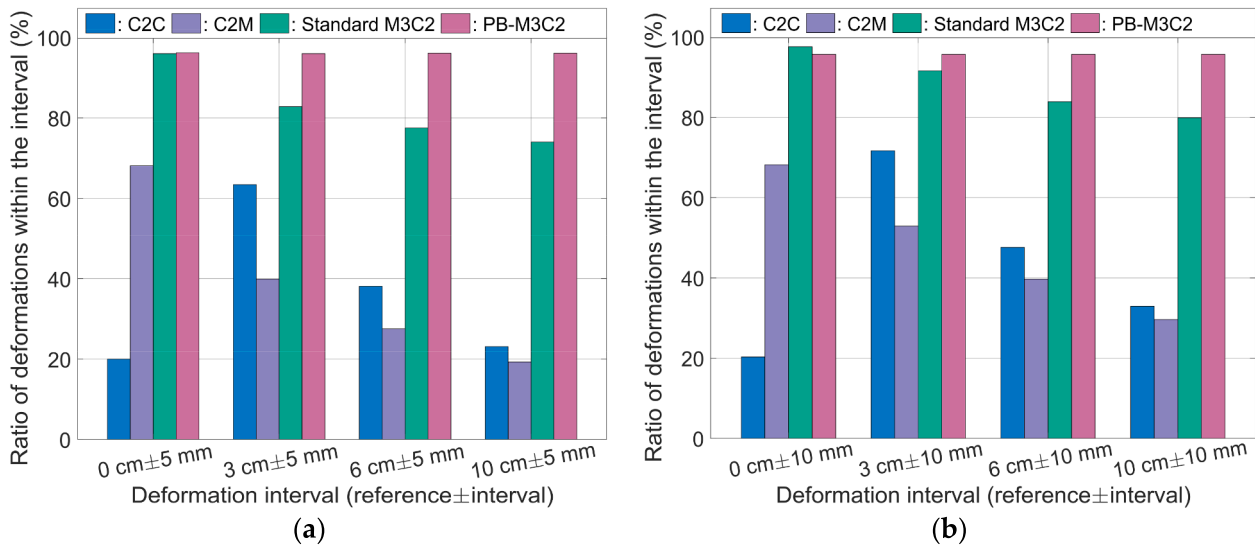


Fig. 17. The ratio of deformations within specified intervals near the reference: (a) Imposing standard deviation of 5 mm; (b) Imposing standard deviation of 10 mm.

4.3. Current limitations and potential improvements

As stated in Section 4.1, PB-M3C2 directly quantifies the distances along defined directions while cannot detect the deformations parallel to the surface. The distance may not agree with the magnitude of the real displacement when the defined deformation direction deviates from the actual deformation direction. Other approaches should be adopted as alternatives for detecting such changes (e.g., feature-based methods).

Similar to standard M3C2 and CD-PB M3C2, the proposed PB-M3C2 also estimates the standard deviation of a selected local area as the empirical uncertainty for determining LoDetection. Since the local modeling of each patch is based on the local consistency assumption, equal weight is imposed on each point for a least squares-based plane fitting. However, realistic uncertainties of the point cloud may not be subject to a strict Gaussian distribution and thus not agree with the empirical estimation. Moreover, systematic errors are not considered in PB-M3C2. In these cases, the modeled patch planes would deviate from the actual surface, resulting in inaccurate distance calculation between associated projected points. A more realistic stochastic model of the point cloud acquired by other approaches (e.g., functional models (Kerekes and Schwieger, 2020) or empirical models (Wujanz et al., 2017)) can be utilized to improve the fitting accuracy of patch planes.

As discussed in Section 4.2, the patches with incomplete boundary separation will yield inaccurate patch planes and overestimated local uncertainties. Besides, overlapping polygons from the convex hulls of adjacent patches make deformation calculations ambiguous in these areas. In this case, a combination of convex and concave polygons can be considered to weaken this impact (Wei, 2008).

In the workflow of PB-M3C2, modules like patch generation and the definition of deformation direction could be further improved independently. For example, with the rapid progress of deep learning, learning-based patch generation methods could be integrated into our pipeline (Landrieu and Boussaha (2019)). In addition, more advanced approaches can also be introduced for the automatic and reliable determination of deformation directions (Williams et al., 2021).

5. Conclusions

In this article, we propose a novel deformation analysis method for 3D point clouds, called patch-based M3C2, based on the basic framework of the M3C2 algorithm. Our pipeline is fully automatic and inherits the advantages of standard M3C2. Based on a local consistency assumption for point clouds, discontinuities of surface geometries and

inconsistencies of deformations are separated by utilizing locally planar patches. Then we construct prisms from individual patches instead of the cylinders in standard M3C2 to capture the corresponding points and project them onto associated patch planes. Distances are computed directly between these projected points in prisms rather than the average positions in cylinders, thus avoiding the deviation and over-smoothing effect on deformation quantifications by standard M3C2. We modify the LoDetection in standard M3C2 by using projected standard deviations along defined deformation directions and considering the spatial correlations between measurements within the patch. Experimental validations and evaluations by three datasets in different modalities and scales show significant improvements in deformation quantification and drastic reductions of associated uncertainties achieved by PB-M3C2. In particular, small-magnitude deformations from highly rough surfaces are successfully detected with lower uncertainties compared to standard M3C2.

The potential applications of PB-M3C2 are promising owing to its simplicity for implementation and universality for processing 3D point clouds of any scale or from any sensor, especially for monitoring natural surfaces with complex topographies and dynamics (e.g., landslide and rock glacier, etc.). Possible improvements for current limitations involve using better-performing segmentation strategies for patch generation and the incorporation of a realistic stochastic model in patch modeling.

CRediT authorship contribution statement

Yihui Yang: Conceptualization, Methodology, Software, Investigation, Experiments, Visualization, Writing – original draft, Writing – review & editing. **Volker Schwieger:** Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgement

We would like to thank Prof. Dr. Bernhard Höfle (3D Geospatial Data Processing Research Group, Heidelberg University) for his valuable comments and suggestions on the manuscript. This publication was funded by the German Research Foundation (DFG) grant “Open Access Publication Funding / 2023-2024 / University of Stuttgart” (512689491).

References

- Anders, K., Lindenbergh, R.C., Vos, S.E., Mara, H., De Vries, S., Höfle, B., 2019. High-frequency 3D geomorphic observation using hourly terrestrial laser scanning data of a sandy beach. *ISPRS Ann. Photogram. Remote Sens. Spat. Inf. Sci.* 4 (2/W5), 317–324.
- Aspert, N., Santa-Cruz, D., Ebrahimi, T., 2002. Mesh: Measuring errors between surfaces using the hausdorff distance. In *Proceedings of the IEEE International Conference on Multimedia and Expo.* 1, 705–708.
- Cignoni, P., Rocchini, C., Scopigno, R., 1998. Metro: measuring error on simplified surfaces. *Comput. Graphics Forum.* 17, 167–174.
- DiFrancesco, P.-M., Bonneau, D., Hutchinson, D.J., 2020. The implications of M3C2 projection diameter on 3D semi-automated rockfall extraction from sequential terrestrial laser scanning point clouds. *Remote Sens.* 12, 1885.
- Girardeau-Montaut, D., Roux, M., Marc, R., Thibault, G., 2005. Change detection on points cloud data acquired with a ground laser scanner. *Int. Arch. Photogram. Remote Sens. Spat. Inf. Sci.* 36, 30–35.
- Gojcic, Z., 2021. Benefiting from local rigidity in 3D point cloud processing. ETH Zurich, Zurich, Switzerland. Ph.D. Thesis.
- Gojcic, Z., Zhou, C., Wieser, A., 2020. F2S3: Robustified determination of 3D displacement vector fields using deep learning. *J. Appl. Geod.* 14, 177–189.
- Gojcic, Z., Schmid, L., Wieser, A., 2021. Dense 3D displacement vector fields for point cloud-based landslide monitoring. *Landslides.* 18, 3821–3832.
- Harmening, C., 2020. Spatio-temporal deformation analysis using enhanced B-spline models of laser scanning point clouds. Technische Universität Wien, Vienna, Austria. Ph.D. Thesis.
- Harmening, C., Hobmaier, C., Neuner, H., 2021. Laser scanner-based deformation analysis using approximating B-spline surfaces. *Remote Sens.* 13, 3551.
- Hassan, A., Zhang, L., Kerekes, G., Schwieger, V., 2022. Fusion of inhomogeneous geodetic data for rock cliff monitoring: A case study of the Lianziya cliff in Three Gorges National Geological Park in China. In *Proceedings of the XXVII FIG Congress, Warsaw, Poland, 11–15 September 2022*, pp. 11340.
- Holst, C., Janßen, J., Schmitz, B., Blome, M., Dercks, M., Schoch-Baumann, A., Blöthe, J., Schrott, L., Kuhlmann, H., Medic, T., 2021. Increasing spatio-temporal resolution for monitoring Alpine solifluction using terrestrial laser scanners and 3D vector fields. *Remote Sens.* 13, 1192.
- Holst, C., Kuhlmann, H., 2016. Challenges and present fields of action at laser scanner based deformation analyses. *J. Appl. Geod.* 10, 17–25.
- Holst, C., Nothnagel, A., Haas, R., Kuhlmann, H., 2019. Investigating the gravitational stability of a radio telescope's reference point using a terrestrial laser scanner: Case study at the Onsala Space Observatory 20-m radio telescope. *ISPRS J. Photogram. Remote Sens.* 149, 67–76.
- Kauker, S., Schwieger, V., 2017. A synthetic covariance matrix for monitoring by terrestrial laser scanning. *J. Appl. Geod.* 11, 77–87.
- Kerekes, G., Schwieger, V., 2020. Elementary error model applied to terrestrial laser scanning measurements: Study case Arch Dam Kops. *Mathematics.* 8, 593.
- Kermarrec, G., Kargoll, B., Alkhatib, H., 2020. Deformation analysis using B-spline surface with correlated terrestrial laser scanner observations—A bridge under load. *Remote Sens.* 12, 829.
- Kuhlmann, H., Schwieger, V., Wieser, A., Niemeier, W., 2014. Engineering geodesy—definition and core competencies. *J. Appl. Geod.* 8, 327–334.
- Lague, D., Brodu, N., Leroux, J., 2013. Accurate 3D comparison of complex topography with terrestrial laser scanner: Application to the Rangitikei canyon (NZ). *ISPRS J. Photogram. Remote Sens.* 82, 10–26.
- Landrieu, L., Boussaha, M., 2019. Point cloud oversegmentation with graph-structured deep metric learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. 7440–7449.
- Lane, S.N., Westaway, R.M., Murray Hicks, D., 2003. Estimation of erosion and deposition volumes in a large, gravel-bed, braided river using synoptic remote sensing. *Earth Surf. Processes Landforms.* 28, 249–271.
- Lin, Y., Wang, C., Zhai, D., Li, W., Li, J., 2018. Toward better boundary preserved supervoxel segmentation for 3D point clouds. *ISPRS J. Photogram. Remote Sens.* 143, 39–47.
- Neuner, H., Holst, C., Kuhlmann, H., 2016. Overview on current modelling strategies of point clouds for deformation analysis. *Allgemeine Vermessungs-Nachrichten: AVN.* 123, 328–339.
- Papon, J., Abramov, A., Schoeler, M., Worgotter, F., 2013. Voxel cloud connectivity segmentation-supervoxels for point clouds. In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. 2027–2034.
- Qin, R., Tian, J., Reinartz, P., 2016. 3D change detection—approaches and applications. *ISPRS J. Photogram. Remote Sens.* 122, 41–56.
- Schmitz, B., Kuhlmann, H., Holst, C., 2020. Investigating the resolution capability of terrestrial laser scanners and its impact on the effective number of measurements. *ISPRS J. Photogram. Remote Sens.* 159, 41–52.
- Stilla, U., Xu, Y., 2023. Change detection of urban objects using 3D point clouds: A review. *ISPRS J. Photogram. Remote Sens.* 197, 228–255.
- Teza, G., Galgaro, A., Zaltron, N., Genevois, R., 2007. Terrestrial laser scanner to detect landslide displacement fields: a new approach. *Int. J. Remote Sens.* 28, 3425–3446.
- Travelletti, J., Malet, J.P., Delacourt, C., 2014. Image-based correlation of laser scanning point cloud time series for landslide monitoring. *Int. J. Appl. Earth Obs. Geoinf.* 32, 1–8.
- Wei, S., 2008. Building boundary extraction based on LiDAR point clouds data. *Int. Arch. Photogram. Remote Sens. Spat. Inf. Sci.* 37, 157–161.
- Williams, J.G., Anders, K., Winiwarter, L., Zahs, V., Höfle, B., 2021. Multi-directional change detection between point clouds. *ISPRS J. Photogram. Remote Sens.* 172, 95–113.
- Winiwarter, L., Anders, K., Höfle, B., 2021. M3C2-EP: Pushing the limits of 3D topographic point cloud change detection by error propagation. *ISPRS J. of Photogram. Remote Sens.* 178, 240–258.
- Wujanz, D., Burger, M., Mettenleiter, M., Neitzel, F., 2017. An intensity-based stochastic model for terrestrial laser scanners. *ISPRS J. Photogram. Remote Sens.* 125, 146–155.
- Wunderlich, T., Niemeier, W., Wujanz, D., Holst, C., Neitzel, F., Kuhlmann, H., 2016. Areal deformation analysis from TLS point clouds—The challenge. *Allgemeine Vermessungs-Nachrichten: AVN.* 123, 340–351.
- Xiao, Y., Chen, Z., Lin, Z., Cao, J., Zhang, Y.J., Lin, Y., Wang, C., 2020. Merge-swap optimization framework for supervoxel generation from three-dimensional point clouds. *Remote Sens.* 12, 473.
- Yang, Y., Balangé, L., Gericke, O., Schmeer, D., Zhang, L., Sobek, W., Schwieger, V., 2021. Monitoring of the production process of graded concrete component using terrestrial laser scanning. *Remote Sens.* 13, 1622.
- Zahs, V., Winiwarter, L., Anders, K., Williams, J.G., Rutzing, M., Höfle, B., 2022. Correspondence-driven plane-based M3C2 for lower uncertainty in 3D topographic change quantification. *ISPRS J. Photogram. Remote Sens.* 183, 541–559.
- Zhong, W., Zhang, T., Chen, J., Shang, J., Wang, S., Mu, C., Fan, C., 2021. Seasonal deformation monitoring over thermokarst landforms using terrestrial laser scanning in Northeastern Qinghai-Tibetan Plateau. *Int. J. Appl. Earth Obs. Geoinf.* 103, 102501.